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Transforming Fruit Farming in a hi-tech Way through Remote Sensing: A Review

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ABSTRACT: Horticulture has emerged out as one of the potential agricultural enterprises in accelerating the economic growth. Its role in country's food and nutritional security, poverty alleviation and employment generation programmes is very crucial. Fruit crops are imperative part with its maximum production share in horticultural sector. These crops being capital as well as labour intensive, it is a wise step to use modern technologies for the development of fruit orchards and its true production potential. Remote sensing is a modern tool that can be an effective technology for site specific crop management in present time. Remote sensing is the process of acquiring data or information about objects or substances not in direct contact with the sensor by gathering its inputs using electromagnetic radiation that emanate from the targets of interest. These involves sensing and recording reflected or emitted energy and processing, analysing and applying that information for interpretations. Remote sensing can provide pivotal database for predicting important parameters using various models and tools which can be helpful to maintain potential yield of fruit crops. Careful consideration of sensors, platforms, vegetation indices, models and many other technicalities can make application of RS in fruit crops more effective and reliable. Here, an attempt has been made to address the gap in the use of remote sensing in Indian fruit farming and to offer potential solutions.

Keywords: Crop classification, crop identification, diseases detection, insect-pest infestation estimation, nutrient content estimation, UAV based RS-GIS, vegetation indices, yield estimation.

INTRODUCTION

India is an agricultural country and about 70% of population directly depends on agriculture sector for their livelihood. Indian agriculture has tremendous 19.90% share in country's GDP. Furthermore, with 34.04% share in Indian agricultural GDP, horticulture sector shows its dominance and importance in Indian agriculture. Out of total arable land in India, 17% i.e., 27.20 million ha is occupied by horticultural crops which has 329.86 million tonnes production. Horticulture production boost up 2.05% higher than last year while, 8.50% higher in comparison to last five years (Champaneri *et al.,* 2020). Among horticultural production, fruit crops have gigantic 31% production share in total horticultural produce. India is the second largest producer of fruit crops at global level with 11.38% share in world fruit production. Fruit crop helps to earn Rs. 4,971.22 crores and 3,887.83 crores foreign money via export of fresh fruits and processed fruit products, respectively which plays a significant role in strengthening the Indian economy (APEDA, 2022). If we consider fruit cultivation in India then, fruit crop covers 6.664 million ha area with 99.069 million MT production and 14.870 MT ha^{-1} productivity (Anonymous, 2020). Indian is leading in production of mango, banana, guava, papaya and citrus at world stage. All these data emerged out the importance of fruit crops in Indian horticulture and ultimately in Indian agriculture as well as economy. In covid pandemic era, by considering the importance of vegetables and fruits in human health, the UN General Assembly designated year 2021 as the International Year of Fruits and Vegetables. WHO currently recommends 120 g or five servings of 20 g of fruits consumption/capita/day which shows the importance of fruit crops in healthy human lifestyle (FAO, 2020).

Population of globe will be going to touch nearly 10 billion bar by the year 2050 and to feed this huge living entity we need 70% of extra food. But agricultural land is decreasing at the rate of 0.03 m ha year^{-1} and according to the reports (Champaneri and Patel 2022). Employment in agricultural sector declined from 81 % in 1983 to 58 % in 2018. While, non-agricultural employment increased from 19 % to 42 % during the same period (Singh *et al.,* 2021). Considering this scenario to get 70 % extra food with existing resources with limited manpower, precision fruit farming is a necessary step to maintain higher yield potential in fruit crops.

Cultivation of fruit crops is highly based on various components of fruit production *viz*., favorable climatic conditions, adequate amount of nutrient supply, irrigation, site specific plant management, harvesting at proper time and many more. These all components contribute equally to get potential yield of any fruit crop. Global warming and climate change does not allow favorable climatic conditions for optimum and quality fruit production. Unjudicial application of nutrients and irrigation leads to abnormal and malform growth of plant. Lack of site specific plant management practices due to shortage of labours increases the occurrence of pests and diseases which ultimately leads to huge yield loss. Delay in harvesting of fruit leads to poor quality of produce along with significant increase in post-harvest loss. As per the reports, collectively all these factors reduce yield of fruit crops at extent of 10 - 100%.

Remote sensing as a tool of precision farming can effectively tackle the hurdles of fruit cultivation. Implementation of remote sensing is highly based on several technical aspects. Developing country like India is lacking in such technical aspects and skill for effective application of remote sensing in agricultural sector. Developed countries are already implementing these technologies in fruit farming and developing nations can also avail benefits of remote sensing by financial support as well as proactive technical guidance to the farmers which can ultimately increase the productivity of fruit crops (Lamba *et al.,* 2021). This review paper incorporates understanding regarding various components of remote sensing, its principles along with its applications in easy and effective manner.

REMOTE SENSING

Remote sensing (RS) is the process of acquiring data or information about an object that is not in direct contact with the sensor by gathering its inputs using electromagnetic radiation, that emanates from the targets of interest or object. These involves sensing and recording of reflected or emitted energy and further processing, analyzing and applying that information for interpretations (Kumar *et al.,* 2021). Remotely data collection from field of fruit crops with help of any platform e.g., satellite or unmanned aerial vehicle (UAV) is done while applying remote sensing and then after interpretations were made based on data processing and analysis of dataset as per the need. There are several components which plays an important role in successful functionating of remote sensing system *viz.,* energy source or illumination, radiation, environment, object, energy detector (remote sensor), platform, data transmission unit, data receiver unit and data processing unit.

PRINCIPLE OF REMOTE SENSING

The first requirement of remote sensing is to have an energy source which illuminates or provides electromagnetic energy or radiation to the target of interest. Mostly Sun is utilized as source of energy and electromagnetic radiation in remote sensing. Once the radiation makes its way to the object through the atmosphere, it interacts with the target depending on the properties of both the object and the radiation. There are three types of interactions that takes place between radiation and object when radiation is contacted upon the surface of object; absorption occurs when radiation is absorbed by the object while, transmission occurs when radiation passes through the object. Reflection occurs when radiation redirects and projects back from the surface of object. The amount of radiation reflected by the object is utilized in further processing of remote sensing. The radiation scattered back or reflected from the object is collected and recorded by remote sensor. This whole process is called radiation interaction. The radiation recorded by the sensor transmitted in electronic form to a receiving and then processing station at where the data were processed. This process is called data transmission. The processed data and images are then analyzed to extract information about the object. The final step of remote sensing process is applying this extracted information to find the solution to particular problem. This process is collectively called data processing and interpretation. The detailed working principle of remote sensing is demonstrated in Fig. 1.

SENSORS IN REMOTE SENSING

Sensors are the device that receive electromagnetic radiations and converts these radiations into signal that can be recorded or displayed as either numerical data or an image. Microwave radiometer, gravimeter, spectrometer, camera, solid scanner, optical mechanical scanner, laser water depth meter, laser distance meter, radar etc. are various examples of sensors used in remote sensing (Pujar *et al.,* 2017). There are mainly two types of sensors utilized in remote sensing *viz*., passive sensor and active sensor.

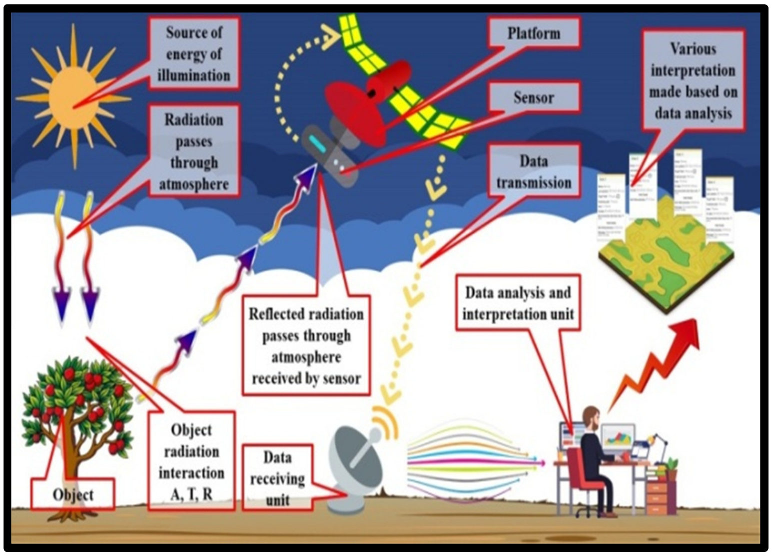

Fig. 1. Principle of remote sensing (A = absorption, T = transmission, R = reflection).

In passive sensor, source of energy or radiation is situated at outside of the sensor. In most of the cases, it is solar energy. Passive sensors can only capture data during daylight hours. The thematic mapper (TM) sensor system on the Landsat satellite is a passive sensor. Unlike passive sensors, active sensors have energy or radiation source situated within the sensor. It can be used without any kind of daylight restriction. Topographic light detection and ranging (LIDAR) laser beam mapping is an example of active sensor (Kumar *et al.,* 2021). Conceptual art depicting the working of passive and active sensor is displayed in Fig. 2.

PLANFORMS IN REMOTE SENSING

Platforms are nothing but vehicles or carriers of remote sensing which carries sensors and other components required for remote sensing. There are mainly three types of platforms used in remote sensing i.e., (1) Ground based, (2) Airborne and (3) Spaceborne. Nowadays UAVs are mostly used in ground based platform. It operates at 10 m to 150 m height. Airborne includes the use of helicopters, jet planes and airplanes which operates at 0.3 to 12 km height. In spaceborne platforms, sensors are mounted on a spacecraft or satellite orbiting the earth. It can acquire imagery of entire earth. It operates at 185 to 900 km height. As height of the platform increases, coverage area also increases but image quality might decrease. UAVs are mostly utilized in farming sector for various aspects and applications of remote sensing. Types and operating height of various platforms used in remote sensing is showed in Fig. 3.

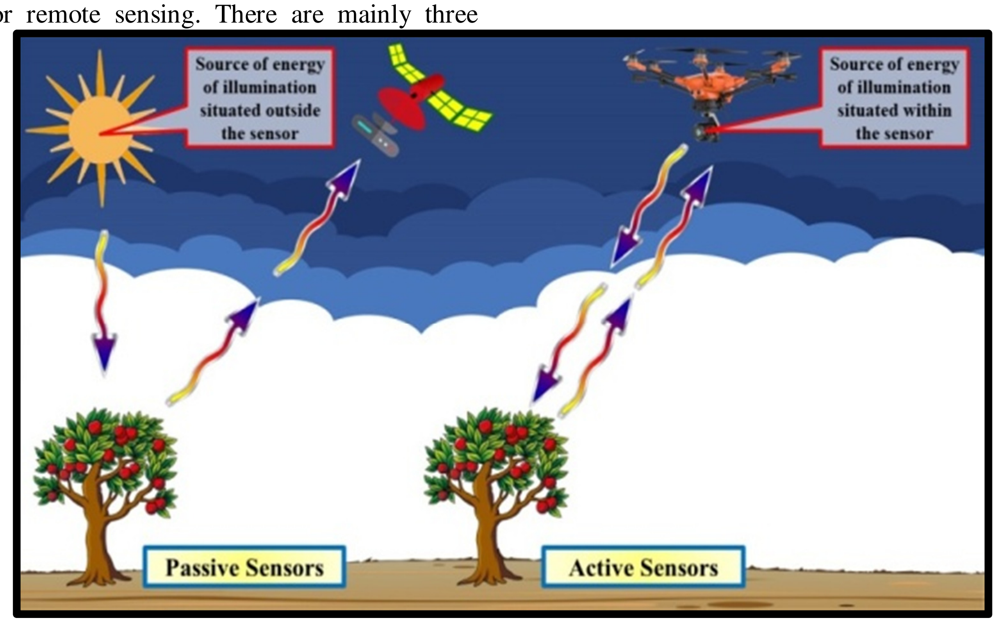

Fig. 2. Illustration of working of passive and active sensor.

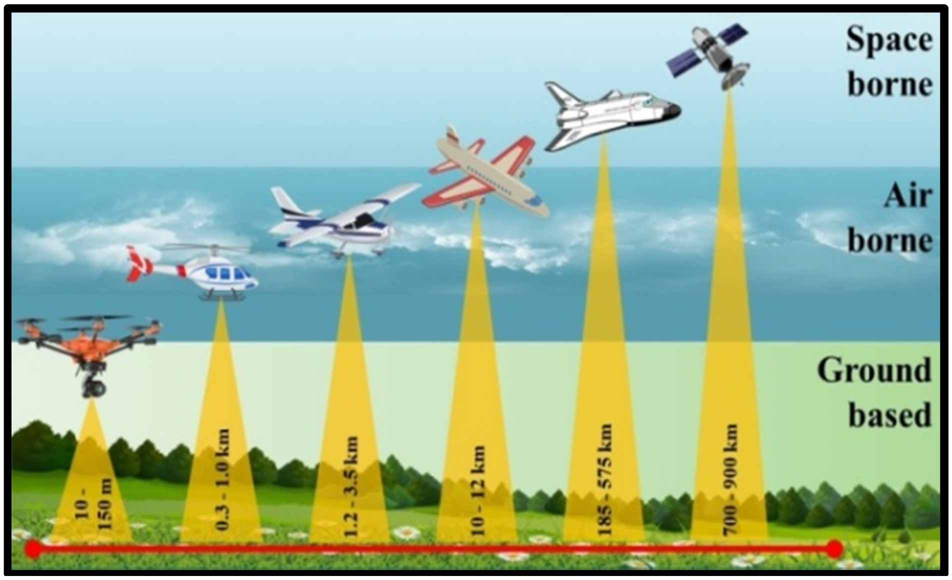

Fig. 3. Types and operating height of various platforms used in remote sensing.

RESOLUTION AND RADIATION IN REMOTE SENSING

Image resolution is the details that an image holds. Higher resolution means more detailed image. In remote sensing mostly four types of resolution are utilized i.e., spatial, spectral, radiometric and temporal. Spatial resolution is the details hold by pixels of an image. It represented by value of pixel e.g., a spatial resolution of 10 m means that one pixel covers 10 m × 10 m of area on the ground. High spatial resolution means more detailed image with smaller pixel size. Whereas, lower spatial resolution means less detailed imagewith larger pixel size. Spectral resolution refers to the ability of a sensor to measure specific wavelength and interval (width) of the electromagnetic spectrum. This refers to the number of bands and width of band in the spectrum. Finer the spectral resolution, narrower the width of band. Multispectral imagery has 3 - 10 bands which are wider. While, hyperspectral imagery has more than hundred numbers of bands which are much narrower so it gives more detailed image in comparison to multispectral imagery. The radiometric resolution of an imaging system describes its ability to discriminate very minute differences in energy with single wavelength at different intensities. Images with low radiometric resolution are able to detect only large differences. While, images with high radiometric resolution are able to detect relatively small differences also. Temporal resolution refers to images of the same geographical area more frequently at specific time interval.

Radiation reflected by the plants depends on the chemical and morphological characteristics of the plant. Plant type, water content, and canopy characteristics affects the light reflected in each spectral band differently. Plants mostly reflects light in ultraviolet, visible (blue, green, red), near to mid - infrared and microwave portions of the spectrum. These are the radiations which are not severely influenced by atmospheric conditions called as atmospheric windows and which are useful for further processing of remote sensing like for calculation of vegetation indices that provide useful information on plant structure and conditions. Various satellite along with resolution details used in horticulture sector are listed in Table 1.

Table 1: Resolutions and applications of satellite used in horticultural sector.

Satellite	Sensors	Spatial Resolution	Temporal Resolution	Application
Landsat 8	MS and thermal	120 m	16 days	Biomass, crop growth, crop yield (Venancio *et al.,* 2019; Dong *et al.,* 2016)
QuickBird	MS	2.44 m	1 - 3.5 days	Disease (Santoso *et al.,* 2011)
WorldView-2	MS	1.40 m	1.1 days	Crop growth (Tian *et al.,* 2017)
WorldView-3	SS	1.24 m	<1 day	Crop growth, weed management (Caturegli *et al.,* 2015; Sidike *et al.,* 2018)
SkySat - 1, SkySat - 2	MS	1 m	sub daily	Crop growth (Ferguson and Rundquist 2018)
Sentinel - 1	C - band SAR	5 - 40	1 - 3 days	Crop growth (He *et al.,* 2018)
Sentinel - 2	MS	10 m - V and NIR, 20 m - Red edge and SWIR, 60 m - 2 NIR	2 - 5 days	Yield, N management (Martínez-Casasnovas *et al.,* 2019; Wolters *et al.,* 2019)
ResourceSat-1	MS	(5.6m - V, 23.5 m - SWIR)	5 days	Nutrient management (Sai and Rao 2008)

VEGETATION INDICES IN REMOTE SENSING

Vegetation indices (VIs) are used as remote sensing indicators. Biophysical features of plants can be characterized spectrally using vegetation indices. Vegetation indices are mathematical expressions that measured reflectance in many spectral bands to produce a value that helps to assess growth, vigor, and several other parameters of plants (Xue and Su 2017). Normalized difference vegetation index (NDVI) is mostly used in agricultural sector for various interpretations. NDVI is based on the amount of absorbed visible red light and reflected near-infrared light. The chlorophyll pigment in a healthy plant absorbs most of the visible red light, while, the cellular structure of a plant reflects most of the near-infrared light and on the basis if these both kind of reflectance, NDVI is calculated. Value of the NDVI result ranges from –1 to 1. Where, dead plants or objects have –1 - 0, unhealthy plants have 0 - 0.33, moderately healthy plants have 0.33 - 0.66 while, very healthy vegetation have 0.66 - 1 values (Gandhi *et al.,* 2015). Example of NDVI is demonstrated in Fig. 4. Different vegetation indices used for estimation of various parameters in farming sector along with their specific equation are listed in Table 2.

Table 2: Vegetation indices used in horticultural crops.

VIs	Full form	Use	Equation	References
NDVI	Normalized Difference Vegetation Index	Biomass, breeding, phenotyping, yield, disease, N - management, soil moisture and water stress	$(R_{NIR} - R_{Red}) / (R_{NIR} + R_{Red})$	(Amaral *et al.,* 2015; Schaefer and Lamb 2016; Duan *et al.,* 2017; Ballester *et al.,* 2018; Hassan *et al.,* 2019; Ihuoma and Madramootoo 2019)
NDRE	Normalized Difference Red Edge	Yield biomass, disease, N - management	$(R_{NIR} - R_{Red\ edge}) / (R_{NIR} + R_{Red\ edge})$	(Kanke *et al.,* 2016; Dadras Javan *et al.,* 2019; Pourazar *et al.,* 2019)
RVI	Ratio Vegetation Index	Crop yield, biomass	R_{NIR} / R_{Red}	(Ranjan *et al.,* 2019; Zhou *et al.*, 2016)
CI_{RE}	Chlorophyll Index	Chlorophyll content	$(R_{NIR} / R_{Red\ edge}) - 1$	Shang *et al.,* 2015
EVI	Enhanced Vegetation Index	Disease and biomass	$2.5\,(R_{NIR} - R_{Red}) / (R_{NIR} + 6R_{Red} - 7.5R_{Blue} + 1)$	(Phadikar and Goswami 2016)
MSAVI	Modified Soil Adjusted Vegetation Index	Biomass, yield, N - uptake, chlorophyll content	$2R_{NIR} + 1 - [2\,(2R_{NIR} + 1)^2 - 8\,(R_{NIR} - R_{Red})]^{1/2} / 2$	(Tahir *et al.,* 2018; Ranjan *et al.,* 2019)
GRVI	Green red vegetation index	Biomass, yield and disease	$(R_{Green} - R_{Red}) / (R_{Green} + R_{Red})$	(Tucker, 1979)
RDVI	Renormalized difference red edge	Biomass, yield, disease, N - management, soil moisture and water stress	$(R_{NIR} - R_{Red\ edge}) / (R_{NIR} + R_{Red\ edge})^{1/2}$	(Robson *et al.,* 2017)
NDSI	Normalized difference spectral index	Nutrient content and chlorophyll content	$(R_{Green} - R_{SWIR}) / (R_{Green} + R_{SWIR})$	(Mahajan *et al.,* 2021)
RSI	Ratio spectral index	Nutrient content and chlorophyll content	(R_{Green} / R_{SWIR})	(Mahajan *et al.,* 2021)
CARI	Carotenoid index	Carotene content	$[R_{Red\ edge} / (R_{Green} - 1)]$	(Zhou *et al.,* 2019)
ARI	Anthocyanin reflectance index	Anthocyanin content	$[(1/R_{Green}) - (1/R_{Red\ edge})]$	Devadas *et al.,* 2009

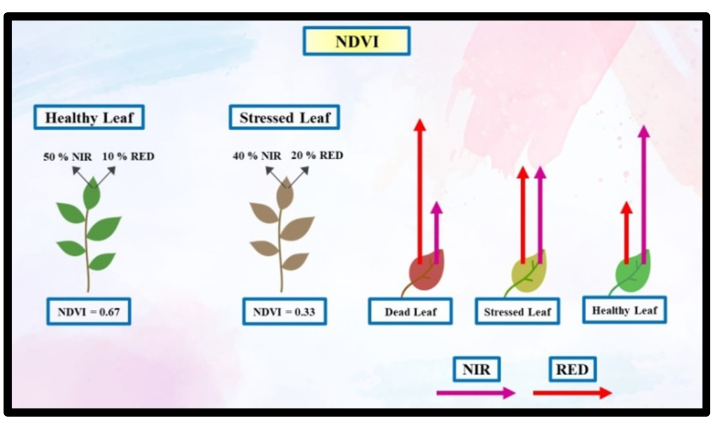

Fig. 4. Example of NDVI.

APPLICATIONS OF REMOTE SENSING

There are various applications of RS in fruit farming. Remote sensing can make crop identification as well as area estimation and mapping quick and easy. Weather forecasting can be done accurately using these technologies. One can improve site specific crop management and can do estimation and prediction of irrigation needs, growth and yield aspects, nutrient requirement as well as pest and diseases infestation.

A. Crop Detection and Classification

Crop detection and classification is one of the most important aspects of utilizing remote sensing in fruit framing. Chaudhari *et al.* (2019) studied on crop inventory of orchard crops in India using remotely sensed data at Space Applications Centre, ISRO, Gujarat. They incorporated linear image self-scanning sensor (LISS - IV) images of ResouceSat along with NDVI and iterative self-organizing data analysis technique (ISODATA) algorithm for classification of various fruits crop. They observed that remotely sensed data has highly acceptable 80% - 98.53 % classification accuracy. Aeberli *et al.* (2021) conducted an experiment on detection of banana plants using multi-temporal multispectral UAV imagery at University of New England, Australia. Convolutional neural network (CNN), template matching (TM) and local maximum filter (LMF) methods were used for plant detection in commercial farm of over 0.5 ha area. The highest F - score of accuracy i.e., 0.93 was noted in CNN method which makes it more reliable. They also estimated plant height and crown spread data with promising 0.80 and 0.85 R^2 values, respectively.

B. Estimation of yield

Implementation of remote sensing in fruit cultivation can accurately estimate plant yield parameters. Sarron *et al.* (2018) conducted a research work on mango yield mapping by UAV at Niayes region of France. They have incorporated UAV acquired RGB imagery, geographic object-based image analysis (GEOBIA) land cover map and canopy height model (CHM) for yield mapping. They estimated plant height with 0.96 R^2 value using CHM model which is based on the subtraction of digital terrain model (DTM) from digital surface model (DSM). They have also predicted mango yield using load index and CHM model with R^2 range of 0.77 - 0.87 for various mango cultivars. Load index is an index which is developed on the basis of quantification of management practices and visual inspection of 150 mango trees. They noted reliable R^2 values for both estimated data for both growth and yield aspects. Rahman *et al.* (2018) in Australia, experimented on high resolution WorldView - 3 (WV3) imagery for estimating yield of mango at University of New England, Australia. They incorporated WV - 3 satellite imagery integrating tree crown area (TCA) using NDVI and renormalized difference vegetation index (RDVI) data as well as artificial neural network (ANN) model. They estimated reliable data for fruit weight of mango with R^2 values of 0.85, 0.79 and 0.93 for orchard 1, 2 and 3, respectively. The observed results were might be due to the reason that they incorporated NDVI and RDVI and after that ANN modelling were applied which ultimately leads to better accuracy of yield mapping.

C. Estimation of nutrients in plant

Mahajan *et al.* (2021) monitored the foliar nutrients status of mango using hyperspectral remote sensing at India. The experiment involved normalized difference spectral index (NDSI), ratio spectral index (RSI) with multiple machine learning (ML) tools and models for prediction, calibration and validation of various nutrients in leaf of mango from 400 samples of 40 orchards. They recorded observe R^2 values of 0.94, 0.91, 0.97, 0.88, 0.90, 0.95, 0.91, 0.80, 0.95, 0.90 and 0.92 for N, P, K, Ca, Mg, S, Fe, Mn, Zn, Cu and B nutrients, respectively, which indicates strong reliability of models. The observed result is might be due to the reason that NDSI and RSI are highly based on radiation emits through vegetation of particular crop and nutrients status highly influence the plant vegetation which ultimately leads to better decision making. Furthermore, use of hyperspectral imaging leads to more accurate tracking of radiation and incorporation of ML tools improves efficiency and reliability of data.

D. Disease detection

Chang *et al.* (2020) carried out research on citrus at Texas A & M University - Corpus Christi, USA to study the application of UAV multispectral images for detection of citrus greening at orchard in Hendry County, Florida, USA. They incorporated four vegetation indices *viz.*, NDVI, normalized difference red edge index (NDRE), modified soil adjusted vegetation index (MSAVI) and red - edge chlorophyll index (CI_{RE}) on 1440 Hamlin citrus trees. They found that CI_{RE} has significantly accurate detection of citrus greening and observed higher difference between citrus greening positive and negative trees in comparison to other VIs because CI_{RE} is sensitive to the changes of chlorophyll content of a plant which is the prominent symptoms of citrus greening. Ye *et al.* (2021) conducted an experiment at Chinese Academy of Sciences, Beijing, China on application of UAV remote sensing in monitoring banana wilt at Guangxi. They incorporated six vegetation indices *viz.*, NDVI, NDRE, green chlorophyll index (CI_{green}), CI_{RE}, anthocyanin reflectance index (ARI) and carotenoid index (CARI) along with various image resolutions *i.e.,* 0.5 m, 1 m, 2 m, 5 m and 10 m. They recorded maximum overall accuracy and kappa coefficient regarding detection of *Fusarium* wilt infestation in banana under CI_{RE} at 0.5 m image resolution. This is might be due to the reason that CI_{RE} are sensitive to the changes of chlorophyll content of a plant, and *Fusarium* wilt infection in banana will cause a decrease in leaf chlorophyll content. Furthermore, it has been widely proved that the red - edge position is very sensitive to changes of the plant chlorophyll content therefore in comparison to VIs without the red - edge band, VIs with the red - edge band had higher overall accuracy and Kappa coefficients. Furthermore, the reason behind good detection of wilt at 0.5 m resolution is lower pixel size which ultimately leads to better quality image.

E. Estimation of irrigation requirement

Hunink *et al.* (2015) studied on estimation of irrigation water applied in fruit crops at Campo de Cartagena district, Spain through remote sensing. They use NDVI for estimating crop evapotranspiration and on the basis of this they estimated the irrigation water applied for particular crop and observed minimum deviation between survey and satellite remote sensing based water application. The observed result is might be due to the fact that the spatial resolution of the NDVI is suitable for certain agricultural water management applications as water status of the plan highly influence the crop vegetation which is accurately detect by NDVI.

CONCLUSIONS

Remote sensing can play a vital role in precision fruit farming. This technology can effectively address the challenges of fruit cultivation and play a pivotal role for increment in fruit productivity. Implementation of UAV based hyperspectral remote sensing along with appropriate vegetation indices and artificial intelligence based machine learning analysis can accurately estimate or predict data in the aspects of plant classification, growth, yield, infestation and other parameters which can pave a path for effective farm planning and successful fruit production. Use of remote sensing in fruit farming is highly relatable with particular growing conditions and parameters to be estimated. Precise technical knowledge and accurate handling of all the components in remote sensing along with adequate dataset is necessary for successful application of remote sensing in fruit crops. Furthermore, the positive impact and benefits of remote sensing are more justifiable in large scale and repetitive site specific crop management. Proactive participation as well as financial aid from government and allied sector can promote successful and effective application remote sensing in developing countries. Change of mindset regarding use of latest technologies in agricultural sector along with work in regards to train manpower along and financial support is necessary for easy adoption of technology. Concrete research work and development of productive data base as well as standard crop specific methods in the aspects of remote sensing approach in fruit farming is necessary task for transferring these technologies from lab to land.

Author contributions. This work was carried out in collaboration among all authors. Author DDC has conceptualized the manuscript, collected the data and prepared the first draft. Authors KDD and TRA has reviewed and edited the manuscript. Author NKP has helped in concept framework and improvement.

REFERENCES

Aeberli, A., Johansen, K., Robson, A., Lamb, D. W. and Phinn, S. (2021). Detection of Banana Plants Using Multi-Temporal Multispectral UAV Imagery. *Remote Sensing, 13*(11), 2123.

Amaral, L. R., Molin, J. P., Portz, G., Finazzi, F. B. and Cortinov, L. (2015). Comparison of Crop Canopy Reflectance Sensors Used to Identify Sugarcane Biomass and Nitrogen Status. *Precision Agriculture, 16*(1), 15-28.

Anonymous (2020). Agriculture Research Data Book. ICAR, New Delhi, 1-330.

APEDA (2022). https://apeda.gov.in/apedawebsite/

Ballester, C., Zarco-Tejada, P. J., Nicolás, E., Alarcón, J. J., Fereres E, Intrigliolo, D. S. and Gonzalez-Dugo, V. J. P. A. (2018). Evaluating the Performance of Xanthophyll, Chlorophyll and Structure-Sensitive Spectral Indices to Detect Water Stress in Five Fruit Tree Species. *Precision Agriculture, 19,* 178-193.

Caturegli, L., Casucci, M., Lulli, F., Grossi, N., Gaetani, M., Magni, S., Bonari, E. and Volterrani, M. (2015). GeoEye-1 Satellite Versus Ground-Based Multispectral Data for Estimating Nitrogen Status of Turfgrasses. *International Journal of Remote Sensing, 36*(8), 2238-2251.

Champaneri, D. D. and Patel, N. K. (2022). Photo Selective Shade Net: An Effective Tool to Reduce the Impact of Global Warming and Pesticide Residues in Vegetable Production: A Review. *Agricultural Reviews, 43*(2), 135-144.

Champaneri, D. D., Patel, N. K., Desai, C. S. and Tandel, B. M. (2020). Economics of Indian bean [*Lablab purpureus* (L.) Sweet] production influenced by application of novel organic liquid nutrient and novel plus organic liquid nutrient. *Asian Journal of Agricultural Extension, Economics and Sociology, 38*(9), 121-126.

Chang, A., Yeom, J., Jung, J. and Landivar, J. (2020). Comparison of Canopy Shape and Vegetation Indices of Citrus Trees Derived from UAV Multispectral Images for Characterization of Citrus Greening Disease. *Remote Sensing, 12*(24), 4122.

Chaudhari, K., Nishant, N., Upadhyay, G., More, R., Singh, N., Vyas, S. P. and Bhattacharya, B. K. (2019). Crop Inventory of Orchard Crops in India Using Remotely Sensed Data. The International Archives of the Photogrammetry. *Remote Sensing and Spatial Information Sciences, 3* (6), 269-275.

Dadrasjavan, F., Samadzadegan, F., Pourazar, S. H. S. and Fazeli, H. (2019). UAV-Based Multispectral Imagery for Fast Citrus Greening Detection. *Journal of Plant Diseases and Protection, 126*, 307-318.

Devadas, R., Lamb, D. W., Simpfendorfer, S. and Backhouse, D. (2009). Evaluating Ten Spectral Vegetation Indices for Identifying Rust Infection in Individual Wheat Leaves. *Precision Agriculture, 10,* 459-470.

Dong, T., Liu, J., Qian, B., Zhao, T., Jing, Q., Geng, X., Wang, J., Human, T. and Shang, J. (2016). Estimating Winter Wheat Biomass by Assimilating Leaf Area Index Derived from Fusion of Landsat-8 and MODIS Data. *International Journal of Applied Earth Observation and Geoinformation, 49*, 63-74.

Duan, T., Chapman, S.C., Guo, Y. and Zheng, B. (2017). Dynamic Monitoring of NDVI in Wheat Agronomy and Breeding Trials Using an Unmanned Aerial Vehicle. *Field Crops Research, 210,* 71-80.

FAO (2020). Fruit and vegetables - your dietary essentials. The International Year of Fruits and Vegetables, 2021, background paper.

Ferguson, R. and Rundquist, D. (2018). Remote Sensing for Site-Specific Crop Management. In: Shannon, D.K., Clay, D.E. and Kitchen, N.R. (Eds.), Precision Agriculture Basics. American Society of Agronomy Crop Science Society of America Soil Science Society of America, USA, 103-117.

Gandhi, M. G. Parthiban, S., Thummalu, N. and Christy, A. (2015). NDVI: Vegetation Change Detection Using Remote Sensing and GIS - A Case Study of Vellore District. *Procedia Computer Science, 57,* 1199-1210.

Hassan, M. A., Yang, M., Rasheed, A., Yang, G., Reynolds, M., Xia, X., Xiao, Y. and He, Z. (2019). Rapid Monitoring of NDVI Across the Wheat Growth Cycle for Grain Yield Prediction Using a Multi-Spectral UAV Platform. *Plant Science, 282,* 95-103.

He, L., Hong, Y., Wu, X., Ye, N., Walker, J.P. and Chen, X. (2018). Investigation of SMAP Active-Passive Downscaling Algorithms Using Combined Sentinel-1 SAR and SMAP Radiometer Data. *IEEE Transactions on Geoscience and Remote Sensing, 56*(8), 4906-4918.

Hunink, J. E., Contreras, S., Soto-Garcia, M., Martin-Gorriz, B., Martinez-Alvarez, V. and Baille, A. (2015). Estimating groundwater use patterns of perennial and seasonal cropsin a Mediterranean irrigation scheme, using remote sensing. *Agricultural Water Management, 162*, 47-56.

Ihuoma, S. O. and Madramootoo, C. A. (2019). Sensitivity of Spectral Vegetation Indices for Monitoring Water Stress in Tomato Plants. *Computers and Electronics in Agriculture, 163*, 104860.

Kanke, Y., Tubana, B., Dalen, M. and Harrell, D. (2016). Evaluation of Red and Red-Edge Reflectance-Based Vegetation Indices for Rice Biomass and Grain Yield Prediction Models in Paddy Fields. *Precision Agriculture, 17,* 507-530.

Kumar, A. L., Tanuja, P., Reddy, P. M. and Chaithanya, K. (2021). Remote Sensing in Fruit Crops. In: Ahirwar, K. (Ed.), Research Trends in Horticulture Science. Akinik Publications, New Delhi, India, 63-77.

Lamba, S., Rani, S. and Kumar, N. (2021). Application of innovative space technology approaches to the sustainability of agricultural systems in the developing world. *Remote Sensing Letters, 12*(4), 315-324.

Mahajan, G. R., Das, B., Murgaokar, D., Herrmann, I., Berger, K., Sahoo, R. N., Patel, K., Desai, A., Morajkar, S. and Kulkarni, R. M. (2021). Monitoring the Foliar Nutrients Status of Mango Using Spectroscopy-Based Spectral Indices and PLSR-Combined Machine Learning Models. *Remote Sensing, 13*(4), 641.

Martínez-Casasnovas, J. A., Uribeetxebarría, A., Escolà, A. and Arnó, J. (2019). Sentinel-2 Vegetation Indices and Apparent Electrical Conductivity to Predict Barley (*Hordeum vulgare* L.) Yield. In: Stafford, J.V. (Ed.), Precision Agriculture. Wageningen Academic Publishers, Wageningen, The Netherlands, 415-421.

Phadikar, S. and Goswami, J. (2016). Vegetation Indices Based Segmentation for Automatic Classification of Brown Spot and Blast Diseases of Rice. In: Proceedings of the *3rd International Conference on Recent Advances in Information Technology (RAIT),* Dhanbad, India, 284-289.

Pourazar, H., Samadzadegan, F. and Javan, F. D. (2019). Aerial Multispectral Imagery for Plant Disease Detection: Radiometric Calibration Necessity Assessment. *European Journal of Remote Sensing, 5*(3), 17-31.

Pujar, D. U., Pujar, U. U., Shruthi, C. R., Wadagave, A. and Chulaki, M. (2017). Remote Sensing in Fruit Crops. *Journal of Pharmacognosy and Phytochemistry, 6*(5), 2479-2484.

Rahman, M. M., Robson, A. and Bristow, M. (2018). Exploring the Potential of High Resolution WorldView-3 Imagery for Estimating Yield of Mango. *Remote Sensing, 10*(12), 1866.

Ranjan, R., Chandel, A. K., Khot, L. R., Bahlol, H. Y., Zhou, J., Boydston, R. A. and Miklas, P. N. (2019). Irrigated Pinto Bean Crop Stress and Yield Assessment Using Ground Based Low Altitude Remote Sensing Technology. *Information Processing in Agriculture, 6*(4), 502-514.

Robson, A., Rahman, M. M. and Muir, J. (2017). Using Worldview Satellite Imagery to Map Yield in Avocado (*Persea americana*): A Case Study in Bundaberg, Australia. *Remote Sensing, 9*, 1223.

Sai, M. S. and Rao, P. N. (2008). Utilization of ResourceSat-1 Data for Improved Crop Discrimination. *International Journal of Applied Earth Observation and Geoinformation, 10*(2), 206-210.

Santoso, H., Gunawan, T., Jatmiko, R. H., Darmosarkoro, W. and Minasny, B. (2011). Mapping and Identifying Basal Stem Rot Disease in Oil Palms in North Sumatra with QuickBird Imagery. *Precision Agriculture,12,* 233-248.

Sarron, J., Malezieux, E., Sane, C.A.B. and Faye, E. (2018). Mango Yield Mapping at the Orchard Scale Based on Tree Structure and Land Cover Assessed by UAV. *Remote Sensing, 10*(12), 1900.

Schaefer, M. T. and Lamb, D. W. (2016). A Combination of Plant NDVI and LiDAR Measurements Improve the Estimation of Pasture Biomass in Tall Fescue (*Festuca arundinacea* var. *Fletcher*). *Remote Sensing, 8*(2), 109.

Shang, J., Liu, J., Ma, B., Zhao, T., Jiao, X., Geng, X., Human, T., Kovacs, J. M. and Walters, D. (2015). Mapping Spatial Variability of Crop Growth Conditions Using RapidEye Data in Northern Ontario, Canada. *Remote Sensing of Environment, 168*, 113-125.

Sidike, P., Sagan, V., Maimaitijiang, M., Maimaitiyiming, M., Shakoor, N., Burken, J. and Fritschi, F. B. (2018). dPEN: Deep Progressively Expanded Network for Mapping Heterogeneous Agricultural Landscape

Using WorldView-3 Satellite Imagery. *Remote Sensing of Environment, 221*, 756-772.
Singh, A., Mehrotra, R., Rajput, V. D., Dmitriev, P., Singh, A. K., Kumar, P., Tomar, R. S., Singh, O. and Singh, A. K. (2022). Geoinformatics, Artificial Intelligence, Sensor Technology, Big Data. In: Kumar, P., Pandey, A., Singh, S.K., Singh, S. and Singh, V. (Eds.), Sustainable Agriculture Systems and Technologies.
Tahir, M. N., Naqvi, S. Z. A., Lan, Y., Zhang, Y., Wang, Y., Afzal, M., Cheema, M. J. M. and Amir, S. (2018). Real Time Estimation of Chlorophyll Content Based on Vegetation Indices Derived from Multispectral UAV in the Kinnow Orchard. *International Journal of Precision Agricultural Aviation, 1*(1), 4-32.
Tian, J., Wang, L., Li, X., Gong, H., Shi, C., Zhong, R. and Liu, X. (2017). Comparison of UAV and WorldView-2 Imagery for Mapping Leaf Area Index of Mangrove Forest. *International Journal of Applied Earth Observation and Geoinformation, 61*, 22-31.
Tucker, C. J. (1979). Red and Photographic Infrared Linear Combinations for Monitoring Vegetation. *Remote Sensing of Environment 8*(2), 127-150.
Venancio, L. P., Mantovani, E. C., do Amaral, C. H., Neale, C. M. U., Gonçalves, I. Z., Filgueiras, R. and Campos, I. (2019). Forecasting Corn Yield at The Farm Level in Brazil Based on the FAO-66 Approach and Soil-Adjusted Vegetation Index (SAVI). *Agricultural Water Management, 225*, 105779.
Wolters, S., Söderström, M., Piikki, K. and Stenberg, M. (2019). Near-Real Time Winter Wheat N Uptake from A Combination of Proximal and Remote Optical Measurements: How to Refine Sentinel-2 Satellite Images for Use in A Precision Agriculture Decision Support System. In: Stafford, J.V. (Ed.), Precision Agriculture. Wageningen Academic Publishers, Wageningen, The Netherlands, 1001-1007.
Xue, J. and Su, B. (2017). Significant Remote Sensing Vegetation Indices: A Review of Developments and Application. *Journal of sensors, 1353691,* 1-17.
Ye, H., Huang, W., Huang, S., Nie, C., Guo, J. and Cui, B. (2021). Application of UAV remote sensing in monitoring banana fusarium wilt. In: Marghany, M. (Ed.), Remote Sensing. Intech Open Limited, London, 1-16.
Zhou, L., Chen, N., Chen, Z. and Xing, C. (2016) ROSCC: An Efficient Remote Sensing Observation-Sharing Method Based on Cloud Computing for Soil Moisture Mapping in Precision Agriculture. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 9*, 5588-5598.
Zhou, X., Huang, W., Zhang, J., Kong, W., Casa, R. and Huang, Y. (2019). A Novel Combined Spectral Index for Estimating the Ratio of Carotenoid to Chlorophyll Content to Monitor Crop Physiological and Phenological Status. *International Journal of Applied Earth Observation and Geoinformation, 76,* 128-142.

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